Herding and Threshold Behavior within a Microscopic Stock Market
The Introduction of Thresholds and a New Switching Mechanism to the Frankfurt Artificial Stock Market

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Summary. Herding combined with threshold behavior is introduced to the Frankfurt Artificial Stock Market in the form of a new kind of so called retail agents. Retail agents remain inactive for most of the time and are only activated if an individual threshold of price increases at the exchange is reached. Once activated they imitate profitable strategies of their neighboring agents. Initiated through heavy losses and falling short of cost prices they sell their shares and fall into hibernation and restart their cycle after an individual number of trading days. The relation between the behavior of the retail agents and the stylized facts of the capital markets will be the center of our study.\footnote{Submitted for participation on the ECCS Satellite Conference ‘Workshop on Heterogeneous Agent Systems and Complex Networks’ organized by Akira Namatame, Enrico Scalas, Taisei Kaizoji.}

1 Introduction

Herding seems to be a widely accepted phenomenon of financial markets \cite{10} \cite{6}. It may be able to explain anomalies like excess volatility. Artificial stock markets like the ones in Cont \& Bouchaud \cite{1} and Lux \& Marchesi \cite{9} are using herding by clustering types of agents that act in concert. Agents may switch their type from either fundamental to noise trader or vice versa.

The more recent Ghoulimie-Cont-Nadal-model \cite{2} explicitly studies threshold behavior of agents and their relation to the stylized facts of the capital
markets. The model leads to the conclusion, that even homogeneous agents without herding effects, but with individual volatility dependent activation thresholds, may produce the stylized facts.

Herding effects through communication within network topologies is the main emphasis of the Frankfurt Artificial Stock Market (FASM) [3]. It was found that networks with a higher degree of centralization lead to higher volatility and distortion in the resulting time series. The model fell short of volatility clustering and volatility-volume-correlation. Inspired by the Ghoulimie-Cont-Nadal-model [2], we extend the FASM by individual activation thresholds that depend not on volatility, but on absolute profits within a time window. Furthermore, we introduce a new kind of switching mechanism. Within many existing models the switching takes place between fundamental and noise trader strategies [7]. We are using a new switching mechanism between no rule and either the fundamental or noise trader rule. We are trying to incorporate the behavior of uninformed traders also called retail investors, that only enter the market, when a certain profit threshold is reached and leave the market as soon as losses in relation to their average inventory price occur. We assume that retail investors don’t have any rule by themselves, but herd according to their successful local neighborhood.

2 The Frankfurt Artificial Stock Market with Activation Thresholds and a New Switching Mechanism

The Frankfurt Artificial Stock Market was designed to study how different communication network topologies affect the properties of the resulting time series of prices [3] and if a modified version of the Tobin tax is able to reduce the volatility of prices [4]. Two types of trading strategies, namely the fundamental strategy and the trend oriented strategy, as used in other models [7], propagate according to their actual performance, through a communication network. The amount of agents applying one of the strategies vary according to the profitability of the strategies. The course of the price building process depends mostly on the inner value of the stock, which is an IID Gaussian random variable, and on the number of agents using the trend or fundamental strategy.

We decided to extend the existing FASM model in the direction of activation thresholds and invented a new switching algorithm. We hope for a closer fit to the stylized facts and think that we achieved a better degree of plausibility for our assumptions.

Besides the two traditional agent types fundamental and noise, we are using a new kind of agent, calling it retail agent. The intention is to model the vast numbers of uninformed and mostly inactive investors, that may play a role especially in extreme valuation situations. To the knowledge of the authors, there is no empirical data yet that describes the behavior of such investors. Kumar and Lee [8] showed that individual investors tend to act in concert and
that a relation between sentiment and return formation exists. Nevertheless, introducing a retail agent to the FASM was more the consequence of personal observations of the authors.

The retail agent is endowed with the ability to adopt both strategy types and acts on activation threshold. While initial noise and fundamental agents never switch their strategy. In contrast to the Ghoulmie-Cont-Nadal-model [2], the authors opted for an activation threshold in relation to absolute profit within a time window and not to volatility. For uniformed investors absolute profit seemed to be more suitable than volatility. As for most retail investors stock market transactions are mostly only a secondary income stream, it should be possible to refrain from transactions if experiences suggest. Therefore, retail agents are initially inactive and without a trading strategy. They get activated, if an individual threshold of price increases at the exchange is reached. Once activated retail agents look out for promising trading strategies within their direct neighborhood.

Three cases are possible:

1. All direct neighbors are retail agents, none of them has yet acquired a trading strategy.
2. One of the direct neighbors has a trading strategy, that was successful within a specific time frame.
3. Several direct neighbors are using different trading strategies.

In the first case the retail agent remains active, but refrains from trading, because of the lack of any trading strategy. In the second case, there is one agent in the direct neighborhood with a trading strategy. If the strategy has been successful within a time window, the agent adopts the new strategy and starts trading. In the third case there are multiple strategies within the direct neighborhood. In that case the most successful strategy will be adopted and trading starts. See table 1 for a pseudo code description of the mechanism.

For eventually acquiring a trading strategy fundamental and noise agents are needed that exist as two clusters within the network of agents, that is dominated in numbers by inactive retail agents. Fundamental and noise agents never change their strategy and are always active, as it would be expected from institutional investors. Kumar & Lee [8] found in their study that the average trade size of over 60,000 retail investor households is about 9,000 US$. We assumed that the trading volume from institutional investors exceeds the trading volume of individual retail investors by far.

In the course of the simulation the two clusters of fundamental and noise strategies expand and contract their size depending on the deployment of the price building process. They may touch and may conquer the whole network (Figure 1). The contraction of the size of the clusters may be initiated by fundamental agents buying or selling in case of larger misvaluations in relation to the inner value, or the experience of losses for retail agents. The retail agents have been modeled in the way that if the actual price falls short of the average individual inventory price, retail agents start selling their shares
Fig. 1. Three possible agent distributions on a scale-free network [5] (fundamental agents in black, trend oriented agents in gray, retail agents in white). First network shows possible initial distribution. Second network after some simulation interval. Third network with possible full activation of all retail agents.
Herding Agent Behavior
BEGIN
active := FALSE
get cash
WHILE last trading day NOT reached DO
BEGIN
IF \( \Delta(Price, TimeWindow) > Threshold \) OR active THEN
active := TRUE
IF neighbor owns (better) strategy THEN
adopt strategy
start trading
IF Price \(<\) InventoryPrice THEN
active := FALSE
sell all shares
hibernation
END
END

Table 1. Pseudo code of the herding agent

and stop trading for a number of days. They switch to an inactive status for an individual number of days, before they start monitoring the share prices again. They fall back into their initial state, only the amount of cash differs. Depending on the course of the price and the used trading strategies during the activity period, it seems probable, that retail agents end their activity cycle with a cash loss. Empirical evidence from Odean and Barber [11] shows, that retail investors in Taiwan on average lost 2.8% of personal income, when trading at the Taiwan stock exchange. The activity cycle of an retail agent starts again, if the personal activation threshold is reached. The cash drain is compensated during the inactivity and may be seen as earned income.

3 Summary and Outlook

We extended the Frankfurt Artificial Stock Market by the introduction of activation thresholds and retail agents. Retail agents initially don’t follow a trading strategy by themselves, but imitate profitable strategies from their direct neighborhood, once an activation threshold in form of profits at the exchange is reached. Similar to institutional investors, fundamental and noise traders exist within the neighborhood of retail agents, that are always active never change their strategy and are the source of potential trading strategies for retail agents. All types of agents are interconnected by a well defined communications network in the form of a scale-free network [5]. Retail agents are modeled to fall into hibernation as soon as losses from trading occur. After an individual amount of trading days they start again monitoring the prices at the exchange and get activated, once the activation threshold is reached again.
Inspired by the Ghoulmie-Cont-Nadal-model [2] and empirical studies from Kumar & Lee [8] and Odean & Barber [11] the authors want to improve the quality of the resulting time series and increase the plausibility of assumptions through following some results of empirical studies.

The implementations of the model changes have been already completed. Simulations are currently under way to test the sensitivity of the input parameters and to judge the quality of the resulting time series in regard of the stylized facts. By the time of the conference the results of our efforts will be ready for presentation.

References